DTU Library

Benchmarking Heating System Performance in Office Buildings through Grey-box Modeling

Fjerbæk, Esben Visby; Hviid, Christian Anker

Published in:
Journal of Physics: Conference Series

Link to article, DOI:
10.1088/1742-6596/2654/1/012068

Publication date:
2023

Document Version
Publisher's PDF, also known as Version of record

Citation (APA):
Fjerbæk, E. V., & Hviid, C. A. (2023). Benchmarking Heating System Performance in Office Buildings through Grey-box Modeling. *Journal of Physics: Conference Series*, *2654*(1), Article 012068. https://doi.org/10.1088/1742-6596/2654/1/012068

Journal of Physics: Conference Series

PAPER • OPEN ACCESS

Benchmarking Heating System Performance in Office Buildings through Grey-box Modeling

To cite this article: Esben Visby Fjerbæk and Christian Anker Hviid 2023 *J. Phys.: Conf. Ser.* **2654** 012068

Benchmarking Heating System Performance in Office Buildings through Grey-box Modeling

Esben Visby Fjerbæk[1,2], **Christian Anker Hviid**[1]

[1] Department for Civil and Mechanical Engineering, Technical University of Denmark, Kgs. Lyngby, Denmark
[2] Rambøll, Copenhagen, Denmark

E-mail: `evifj@dtu.dk`

Abstract. The transition to renewable energy sources requires that larger shares of heating production should come from heat pumps both on individual level and in district heating networks. The efficiency of heat pumps is highly dependent on the temperature lift. Therefore, it is key to assess the possibilities of low-temperature heating in buildings. This paper proposes a data-driven methodology to analyse and benchmark the performance of radiator heating systems, by estimating parameters for the building's envelope and heating system using Modelica with ModestPy. The methodology requires little a-priori knowledge and common data sources and provide valuable insights on the potentials of lowered operating temperatures. The methodology was tested on a newly renovated office building in Copenhagen and was able to consistently estimate characteristics of the envelope and capacity of the heating system. By using information on the actual capacity of the heating system, the methodology demonstrated the potential for lowering the heating supply temperatures, thereby reducing heat pump electricity consumption with 9 %.

1. Introduction

The efficiency and capacity of heat pumps depend highly on the required temperature lift, which means that there is a large financial and technical incentive to reduce the need for high supply temperature in buildings [1]. However, the potential of reducing the supply temperature is severely impacted by faults and malfunctions in the heating system that impairs the efficiency.

These faults often lead to thermal discomfort and user complaints, because they reduce the actual capacity of radiators. To accommodate complaints, the building operator will often increase the overall supply temperature instead of correcting the faults. The end result is higher operating temperatures than necessary.

To achieve a well-performing space heating system at minimal temperatures, it is necessary to provide a benchmark for the building operator that can be used as a target for efficiency. If the target is not met, faults are potentially present in the heating system preventing efficient heating operation.

This paper proposes a methodology that estimates the actual capacity of the radiators, based on measurement data and little a-priori knowledge. The estimated capacity is then compared to the installed capacity, to benchmark the performance. The methodology builds upon a grey-box modeling (GBM) approach that includes the thermal zone and space heating system. While many researchers have used GBMs to estimate the characteristics of the thermal zone [2, 3, 4], mostly driven by the desire to develop predictive control and balance loads [5], fewer have used GBMs to detect faults and sub-optimal efficiency of space heating system [6, 7].

The methodology is tested to estimate the lumped power of the radiators on a riser in an office buildings. By comparing the estimated power to the installed power, the performance is assesed, and the optimal return temperature is estimated. The model is used to estimate potentials of reducing the heating supply temperature under current and optimal operation. The benefits of a reduced supply temperature is quantified by calculating the improved heat pump COP and the resulting energy savings.

2. Methodology

The aim of the methodology is to estimate parameters related to the envelope and heating system to provide a benchmark for the heating system and assess possibilities for low-temperature heating. The methodology is designed to use easily obtained and common time-series data and building data to make it scalable. Most of the time series data is commonly found and logged in Building Management Systems while others, such as occupancy, require additional sensors. The methodology should be used on separate parts of the building, e.g. for each riser zone where the necessary data can be obtained. The required and estimated data is shown in table 1.

Table 1. Known and estimated data in the methodology.

Known		**Estimates**	
Solar heat (N/S/E/W)	[W]	Solar heat gain coefficient (N/S/E/W)	[-]
Outdoor temperature	[°C]	Thermal resistance of external walls	[W/(m^2 K)]
Occupancy	[persons]	Lumped nominal radiator power	[W]
Ventilation supply air setpoint	[°C]	Maximum pump mass flow	[kg/s]
Ventilation inactive/active	[0-1]	Thermal mass of constructions*	[-]
Heating supply temperature	[°C]	Temperature setpoint	[°C]
Heating return temperature	[°C]		
Indoor temperature	[°C]		
Volume	[m^3]		
Maximum ventilation rate	[m^3/s]		

* As a multiple of the zone volume air mass.

2.1. Grey-box model

We developed two grey-box Modelica models, adapted from the model described by Arendt et al. [8], which utilizes parts of the OU44 Modelica library [9]. This model, seen in figure 1, is used to estimate the building's thermal characteristics and equivalent radiator sizes.

The model is a resistance-capacitance model (R2C2) that represents a generic thermal zone. The solar gains are split into north, south, east and west directions with solar heat gain coefficients (SHGC) for the corresponding facades. The transmission loss is modeled with a single resistance factor, representing all exterior surfaces. The ventilation heat loss is calculated with the maximum of the supply or outdoor temperature and the flow rate.

The heating system is modeled as a lumped radiator and a pump. The distribution system was not modeled, although the flow delay may be important, as this requires too much a-priori knowledge of the building. The radiator is modeled with the *RadiatorEN442_2* model from the Modelica Buildings library [10] with a fixed standard radiator exponent, n, of 1.3. The radiator's nominal power, `nomPower`, is the lumped power output of all radiators with a 70/40/20 temperature set. A proportional controller, with a proportional band of 2 °C, controls the flow through the radiator mimicking the thermostatic radiator valves (TRVs). The flow through the system when the TRVs are fully open is determined by the parameter `maxMassFlow`.

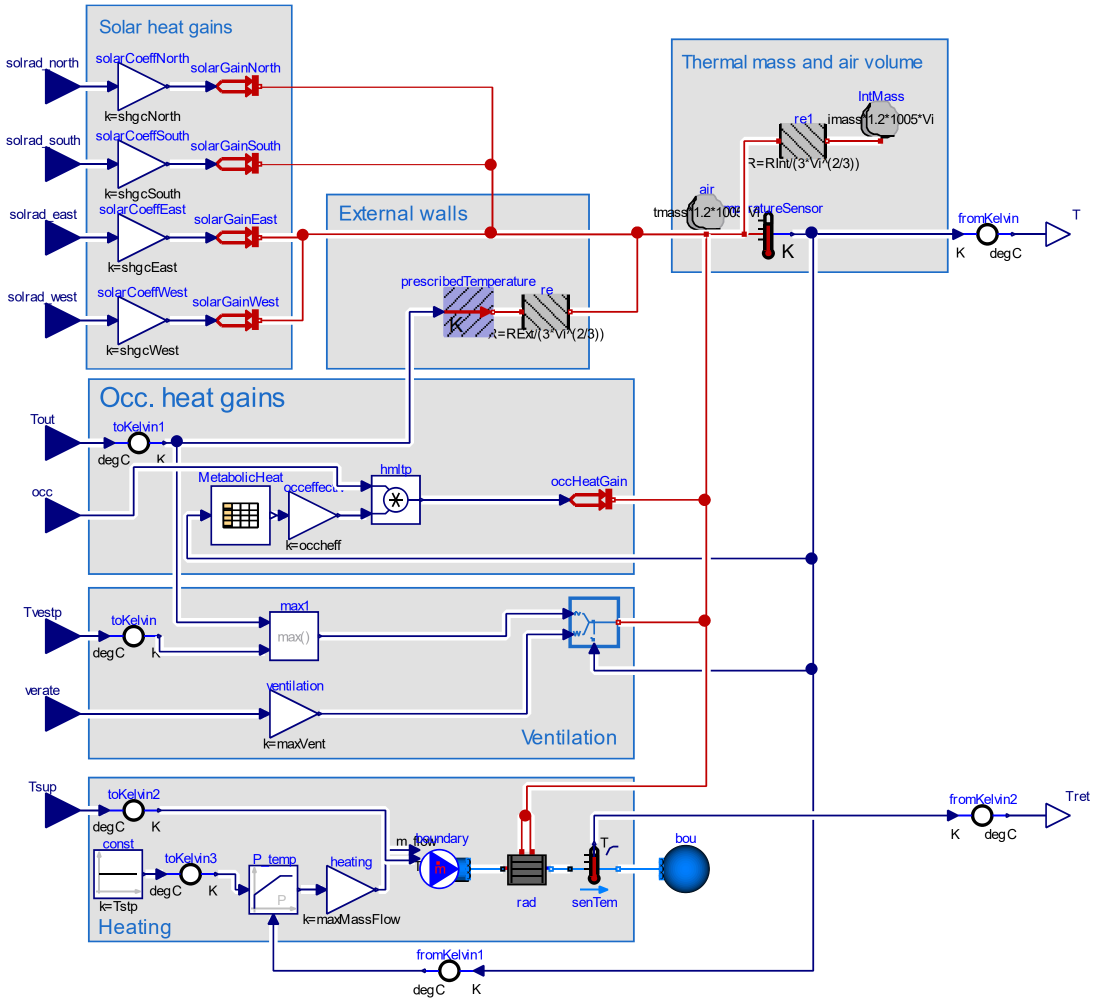

Figure 1. Modelica model for estimation of thermal characteristics of office zone. Adapted from [8].

The model has 9 inputs; `solrad` (one for each orientation) is the solar radiation on a vertical surface in W/m^2, `Tout` is the outdoor temperature in °C, `occ` is the occupancy count, `Tvestp` is the ventilation supply setpoint in °C, `verate` is the on-off signal for the ventilation system (here: constant air volume system) and `Tsup` is the heating supply temperature. The model has two outputs; the room temperature, `T`, and the return temperature, `Tret`, from the heating system.

2.2. Parameter estimation

The parameters of the GBM are estimated using ModestPy, developed by Arendt et al. [8]. ModestPy is a python tool that optimizes parameters in a simulation model defined with the Functional Mockup Interface (FMI) [11] to match chosen measurement data. The optimization can be done through several algorithms distributed with the tool. Multiple algorithms can be combined, e.g. a global search algorithm followed by a local optimization algorithm.

Table 2. Data points in AP15. SH = Space heating.

Point	Level	Frequency	Notes
CO_2	Room	30 min	Averaged value used for model
Temperature	Room	30 min	Averaged value used for model
Occupancy	Building	15 min	Even distribution assumed
Global solar irradiation	Building	15 min	Split into four directions
External temperature	Building	15 min	
SH supply temperature	Riser zone	30 min	
SH return temperature	Riser zone	30 min	
Ventilation rate	Building	-	Not logged. Derived from distributed occupancy and CO_2 levels.
Supply air temperature	Riser zone	-	Not logged. Derived from known weather compensation.
Room temperature setpoint	Riser zone	-	Not logged. Estimated from room temperatures and a p-band of 2 K

3. Case study

3.1. Building

The investigated office building is located in Copenhagen, Denmark, and was renovated in 2020-2021. The building has a floor area of approximately 14'500 m^2, distributed over six stories. The building has three sections (A, B and C) that each has two risers (in the east and west side) with individual supply temperatures. The ventilation system consists of three air handling units, one per section. In the case study, riser zone C east (CE) is considered as a single thermal zone (3'280 m^2) using average temperatures and CO_2 levels. Through a manual investigation of the size and number of radiators, combined with manufacturer data, it was determined that the lumped nominal power of the radiators in zone CE is 22 kW at a temperature set of 70/40/20.

3.2. Data points and processing

Time-series data were gathered partly from the building management system (BMS), and partly from an IOT data platform. Table 2 gives an overview of the data sources, their logging frequency and measuring level (room, zone or building). All data was resampled to align the range and time stamps of all data sources. Moreover, discontinuous data sources, such as the ventilation rate, were smoothened to improve numerical stability.

3.3. Experimental setup

ModestPy includes several algorithms for parameter estimation. We chose the ModestGA algorithm, which is a genetic algorithm (GA) built for ModestPy, combined with the PS algorithm, which is a pattern-search algorithm, also built for ModestPy. Table 3 lists ModestPy input.

Table 3. Algorithm setup for estimation of ventilation rate and thermal characteristics. Refer to ModestPy documentation [8] for a description of the parameters.

ModestGA		PS		Both	
Generations	20	Max. Iterations	40	Runs	10
population size	40	Relative stepsize	0.02	Learning period	Jan 1 - Jan 29
Tournament size	7	Tolerance	1e-03	Cost function	NRMSE
Tolerance	1e-03	Maximum tries	10		

4. Results

The estimated parameters for the building and heating system, including the normalized root-mean-square-error (NRMSE), can be found in table 4. The simulated room and return temperatures have been plotted with the measurements in figure 2. The NRMSE is output from ModestPy and reflects the estimate's overall error related to both the return and room temperature.

Table 4. Estimated parameters and the errors (NRMSE and RMSE).

Parameter	Value	Parameter	Value	Parameter	Value
shgcSouth	20.0	maxMassFlow	0.54	NRMSE	0.092
shgcEast	20.0	imass	18.0	RMSE (T_{room})	0.46
RExt	1.68	nomPower	18.3	RMSE (T_{ret})	3.00

From figure 2 and table 4 it is clear that the room temperature is matched better than the return temperature. The RMSE for the room temperature is 0.46 °C compared to the RMSE of the return temperature of 3.0 °C. In figure 2, it is seen that the simulated return temperature does not always match the measured and that it generally varies more. However, the overall temperature level is acceptable.

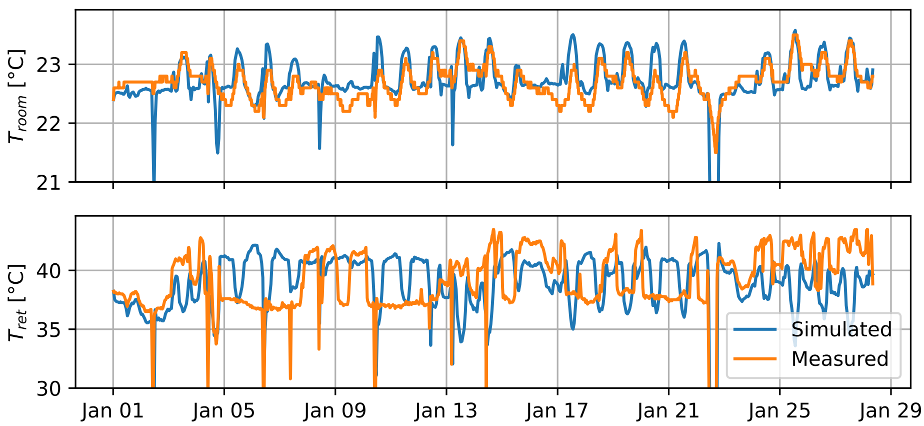

Figure 2. Comparison of measured and simulated results for the thermal characteristics.

4.1. Sensitivity and validity

The ModestGA algorithm is a genetic algorithm, which uses a certain degree of randomness in the optimization process. This means that every time the ModestPy estimation is run, the solution may change because of local minima. To ensure that ModestPy found the most correct result, it was run ten times, as indicated in table 3. The results for `RExt`, `nomPower` and `maxMassFlow` and the resulting error in each run are plotted in figure 3. Figure 3 illustrates that for the runs with the lowest error, the parameter estimations are stable. This indicates that the solution can be trusted and that the best run is not a local minimum.

4.2. Analysis

The parameter estimation finds that the active radiator power is 18.3 kW at a temperature set of 70/40/20. The installed power is 22 kW, and it can be concluded that faults in the

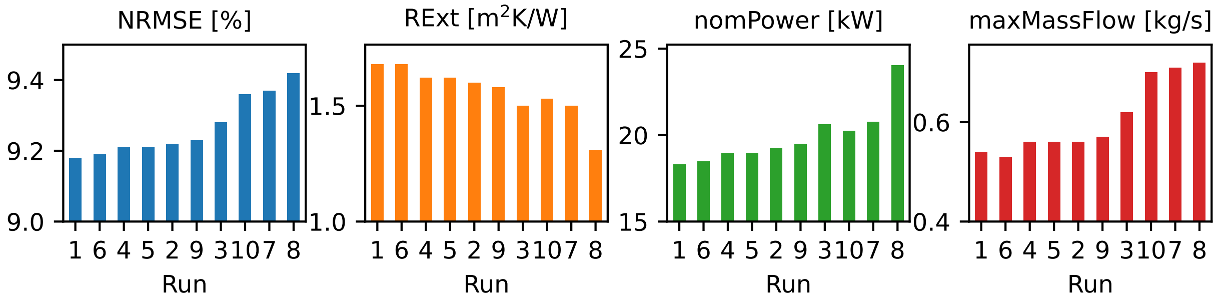

Figure 3. Comparison of ten runs with ModestPy

system or operation cause the radiators to operate at sub-optimal performance, although the faults cannot be identified. To estimate the optimal return temperature, the *Baseline* scenario, which is represented by the GBM with estimated parameters, has been compared to an *Optimal* scenario where the radiator power in the GBM is changed to 22.0 kW. The *Optimal* scenario represents a situation where all faults in the heating system have been corrected to utilize the full capacity of the radiators.

Table 5. Comparison of the four scenarios

	Baseline	Optimal	Baseline -5K	Optimal -5K
Nominal power [kW]	18.3	22.0	18.3	22.0
T_{sup}* avg [°C]	49.8	49.8	44.9	44.9
T_{ret}* avg [°C]	39.3	37.4	37.8	34.0
T_{room} avg [°C]	22.7	22.9	22.1	22.4
Time with max. flow [%]	2	2	46	5

* Energy-weighted

To estimate the potential for reducing the supply temperature, the supply temperatures in the Baseline and Optimal scenarios have been reduced with 5 °C in scenarios *Baseline -5K* and *Optimal -5K*. The results can be seen in table 5. The average outdoor temperature during the investigated period was 4.3 °C.

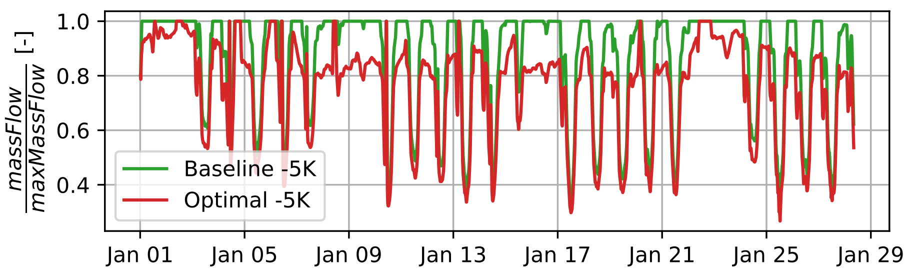

Figure 4. Flow rate ratio $\left(\frac{massFlow}{maxMassFlow}\right)$ in scenarios with lowered supply temperature.

Comparing the *Optimal* scenario with the *Baseline* scenario, the model predicts as expected that fault-corrective actions (yielding higher nominal power) can potentially lower the energy-weighted return temperature by 1.9 °C. Furthermore, in scenario *Optimal -5K*, the supply temperature can be lowered 5 °C without jeopardizing thermal comfort. However, in scenario *Baseline -5K*, the heating system will operate at full mass flow 46% of the time, which means that thermal comfort cannot be maintained. With optimal operation, the system only operates at full mass flow 5% of the time, which means that it can uphold the required comfort temperatures. The radiator flow rate ratio for the low-temperature scenarios throughout the simulation period is shown in figure 4.

4.2.1. Electricity savings potentials Reducing the supply temperature demand with 5 °C, will improve the COP of a heat pump resulting in energy savings. The electricity consumption, W, is found from $W = \frac{Q}{COP}$, where Q is the simulated heat demand. COP was interpolated using the heat pump data in figure 5 for each time step. The result is a reduction from 2583 kWh to 2345 kWh, which is a reduction of 9 % for the investigated time period (average Tout of 4.3 C).

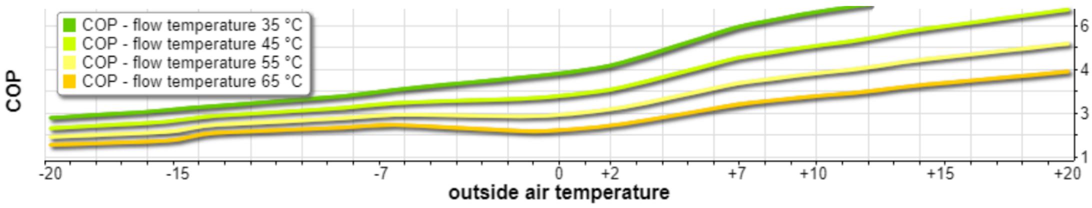

Figure 5. Data sheet for a 27 kW air-to-water heat pump showing COP for outdoor temperature and different heating supply temperatures [12]

5. Discussion

In section 4, the methodology was tested on a real building. Although the building was heavily monitored through BMS and IOT sensors, the required operation data was not directly accessible and some data sources had to be indirectly derived. E.g., the ventilation rate was derived from the assumption that the occupants were evenly distributed in the building. Manual counts of desks confirmed this assumption. Overall, this means that the results may not be of high accuracy, yet it was possible to produce consistent estimates of the building's parameters with low RMSE on indoor temperature. Conversely, the return temperature was estimated with mediocre quality with a significantly higher RMSE of 3 °C. However, simulated and measured return temperatures were in the same range, sometimes higher and sometimes lower, which indicates that the heating system characteristics are not off.

The methodology was able to provide a model for the building and heating system. Since the sizes of the radiators in zone CE were known, it was possible to compare the estimated nominal powers to the actual installed power and estimate the optimal return temperature. If no information about the radiator sizes is available, one approach could be to assess the heating system performance by using the methodology on different parts of a building (e.g., for each riser zone) and compare the estimated nominal powers pr. floor or envelope area across the building to locate inefficient operation. This does not provide an absolute benchmark for the building, but can be useful in identifying local variations which could spark a dedicated effort to obtain the installed nominal power manually.

The analysis showed that offsetting the supply temperature -5 °C would maintain thermal comfort if the radiator system was operated correctly. It may be possible to lower the supply temperature even more if the pump pressure (and thereby flow) can be increased.

Currently, the methodology uses data from each riser zone, which are commonly displayed and logged in BMS systems. However, detailed time-series data of the mass flow rate in the considered riser would significantly benefit the methodology, since it (1) eliminates the need to estimate the maximum pump flow and (2) removes the proportional control of heat flow and uncertainties in room temperature setpoints. This can be achieved with an energy meter for the riser, a dedicated flow meter, or a pump attachment for flow measurements, which are available for some pump models.

6. Conclusion

In this paper, we presented a methodology to estimate the performance of heating systems and the potential for reducing the supply temperature through grey-box modeling. The methodology uses few data sources and a-priori knowledge of the building, with the only non-standard data being the building's occupancy. This means that the methodology is easily scalable to multiple buildings.

The methodology was tested on a case study, where it was used to benchmark the radiator efficiency. With corrective actions, the results showed a potential for 5 °C lower supply and return temperatures. This results in 9% electricity savings when heating is supplied by a heat pump.

While the case study did show promising results for the overall approach, it is clear that the limited data sources influence the validity of the results significantly. Therefore, we recommend adding mass flow for space heating to the data requirements to improve the methodology in future applications.

7. Acknowledgements

The presented work was funded by Elforsk grant no. 352-042 and Innovation Fund Denmark grant no. 2040-00027B. Furthermore, the authors would like to say thank you to the building operators of the case study building.

References

[1] Østergaard D S, Smith K M, Tunzi M and Svendsen S 2022 *Energy* **248** 123529

[2] Bacher P and Madsen H 2011 *Energy and Buildings* **43** 1511–1522

[3] Li Y, O'Neill Z, Zhang L, Chen J, Im P and DeGraw J 2021 *Renewable and Sustainable Energy Reviews* **146** 111174

[4] Yu X, Skeie K S, Knudsen M D, Ren Z, Imsland L and Georges L 2022 *Building and Environment* **212** 108832

[5] Killian M and Kozek M 2016 *Building and Environment* **105** 403–412

[6] Sarran L, Smith K M, Hviid C A and Rode C 2022 *Energy* **261** 125282

[7] Thilker C A, Bacher P, Bergsteinsson H G, Junker R G, Cali D and Madsen H 2021 *Energy and Buildings* **252** 111457

[8] Arendt K, Jradi M, Wetter M and Veje C T 2019 ModestPy: An Open-Source Python Tool for Parameter Estimation in Functional Mock-up Units *Proceedings of The American Modelica Conference 2018, October 9-10, Somberg Conference Center, Cambridge MA, USA* vol 154 pp 121–130

[9] SDU Center of Energy Informatics 2021 OU44 Modelica Library URL `https://github.com/sdu-cfei/OU44`

[10] Wetter M, Zuo W, Nouidui T S and Pang X 2014 *Journal of Building Performance Simulation* **7** 253–270

[11] Blockwitz T, Otter M, Akesson J, Arnold M, Clauss C, Elmqvist H, Friedrich M, Junghanns A, Mauss J, Neumerkel D, Olsson H and Viel A 2012 Functional Mockup Interface 2.0: The Standard for Tool independent Exchange of Simulation Models *Proceedings of the 9th International MODELICA Conference, September 3-5, 2012, Munich, Germany* vol 76 pp 173–184

[12] Heat pump datasheet URL `https://www.wamak.eu/wapps/datasheets/v2019/datasheet.php?standard=1&fsource=A&code=WA001347&lang=en-GB`